

Fast Spammer Detection Using Structural Rank

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Abstract

Comments for a product or a news article are rapidly growing and became a medium of measuring quality products or services. Consequently, spammers have been emerged in this area to bias them toward their favor. In this paper, we propose an efficient spammer detection method using structural rank of author specific term-document matrices. The use of structural rank was found effective and far faster than similar methods.

1 Introduction

Comments are widely growing in web: for a product, a news article, or a sport game. They are usually much shorter than main articles, but large in number with numerous authors. The rich set of responses from varieties of audience, comments, now are analyzed by lots of researchers who believe that they show important aspects of the main article.

Spammers also found the importance of the comments and started to abuse all kinds of comment system and overwhelmed other legitimate comments. They usually exploits the comment system with automatic programs to keep posting their propaganda.

The behavior of the spammers shows a critical point to detect them. Most of their contents are repeated under the same author name. There are sever researches [11, 7, 10, 5] that compute content similarity to detect such spammers. They make use of language model [11], or set intersection similarity [2, 7], or average cosine similarity [10, 5]. In this paper, we will use much faster but an effective method: the structural rank of author specific term-document matrix to detect the spammers.

2 Related Work

Our work is close to social media spam detection as they usually deal with short documents with large number of authors. The approaches are slightly different from traditional spam detection which focuses emails or websites. [6] is a good survey of dealing with spam in social media.

Various content-based features were found effective detecting spams or spammers. [11] used language models to detect spams in blog posts. Bag-of-anchors and bag-of-url were used in [8]. [3] defined folksonomy which are tags co-occurring in network neighbors to detect spammers. [10, 5] computed average all-pair cosine similarity of one specific author with the help of other features.

User networking behavior were also well studied in this area. [9] make use of tagging behavior of a user, such as user concurrence with other spammers. [1] did similar approach categorizing users on Youtube into spammers, promoters, or legitimate users. [12] did similar approach on Twitter. [10] proposed a behavior model adding review score features testing such as its fairness with other features. [5] additionally takes in to account trends of the review (called burstness of review). Graph similarity based detection was used in [14].

3 Structural Rank

The structural rank is the maximum rank of all possible matrices of the same non-zero pattern. Since it only considers the non-zero patterns, we can make use of bipartite graph traverse algorithms for an efficient computation instead of traditional methods for numerical (or theoretical) rank of the matrix. Computing the numerical rank takes $O(mn^2)$ with a matrix $A \in \mathbb{R}^{m \times n}$, $m \geq n$ by computing only singular values using SVD.

There are efficient algorithms computing structural rank [13, 4]. The worst case time complexity was shown $O(\tau n)$ where τ is the number of non-zero entries of the matrix; however, [4] also showed it will run $O(\tau + n)$ in most practices.

The computation benefit is easily noticeable in sparse matrices. In sparse matrices, we know number of non-zero entries are much smaller than the size of the matrix: $\tau \ll mn$. Consequently, $O(\tau n) \ll O(mn^2)$. Moreover, the practical bound $O(\tau + n)$ is obviously smaller than $O(mn^2)$. In section 5.3, we will empirically compare the computation speed.

4 Spammer Detection

4.1 Computing Content Similarity of a Set of Documents

We assume spammers will keep posting similar contents that have similar vocabulary set. If we model comments of a spammer with a term-document matrix (rows as vocabularies and columns as documents), each columns will be similar to each other, and will become linearly dependent to each other. The rank of the term-document matrix will be *relatively* lower than similar size matrix of non-spam user.

There are other ways to compute the similarity metric between columns such as cosine similarity, but traditional metrics usually defined in pairwise and not very intuitive to measure similarities of multiple documents as a whole. Average of all combinations of pairwise cosine similarities was suggested in [10, 5], and it was found effected in detecting spammers. However, this type of approach is much slower than rank based metric since it needs to compute all possible combinations. Given a n documents with m vocabularies (term-document matrix is $\mathbb{R}^{m \times n}$), the average cosine measure needs $O(4m \cdot n^2)$. $4m$ is for a cosine similarity between two documents (note that this will be much slower in sparse vector multiplications), and n^2 is for all

possible pairs. It is indeed slower than computing the structural rank $O(\tau + n)$. See section 5.3 for empirical computation results.

We propose to use structural rank (Section 3) for computing content similarity of a set of documents. 1) Solely considering the non-zero pattern will be enough to measure the content similarity of a set of documents. 2) Term-document matrices are usually very sparse and our case will be even more sparser as we deals with very short documents (comments). Bipartite graph traverse algorithm will be extremely efficient in this case. 3) It will be also much faster than other pairwise based similarity metrics.

4.2 Spammer Score

We propose this *SpammerScore*, which will be use to determine a spammer:

$$SpammerScore(A) = 1 - \frac{StructuralRank(D(A))}{N} \quad (1)$$

where $D(A)$ is a $M \times N$ term-document matrix of author A .

Higher the score, the relative structural rank will be lower, and will be determined as a spammer. For example, if one author keep posting the same contents over and over the score will be $1 - \frac{1}{N}$. The other end will be 0 when an author posted very different postings at each time: $1 - \frac{N}{N} = 0$.

It is noteworthy to mention that our method can also be combined with other types of features such as spam dictionary or user profiles. Our method can be a good add-on features on spam detection systems providing a natural concept of duplicated comments. For example, our method is a good surrogate of average cosine similarity in [10, 5].

5 Experiment

5.1 Dataset

We used NBA dataset for XDATA 2014 challenge¹. The dataset contains 352936 comments from Yahoo sport and ESPN sport website. Comments were from public audience and were responses for NBA games of season 2011-2012~2013-2014 (3481 games). There were 42382 authors and most authors doesn't post much (35K authors have less than 10 comments). Standard preprocessing was performed to generate term-document matrices. We removed all HTML tags, lowercased, tokenized, stemmed, and removed stop words.

5.2 Observations

Figure 1 shows histogram of 42K authors of our dataset. Most of author have *SpammerScore* of 0, but there are also many authors with non-zero *SpammerScore* (1237 authors). Although, the sketchy authors are in small number, they produced a large portion of comments (28% of entire comments). They averagely wrote

¹<http://www.darpa.mil/OpenCatalog/XDATA.html>

6 Discussion

In this paper, we introduced an efficient way detecting spammers by structural rank of per-author term-document matrix. The use of structural rank turned out to be much faster than using traditional rank in our scenario. We hope to extend this line of work to include richer set of features to achieve state-of-the-art spammer detection performance.

We also feel the structural rank needs an additional attention measuring multi-document similarity; for example, evaluating document clusters, document relevance, or in search engines.

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